ADVANCED COMPUTATIONAL INTELLIGENCE STRATEGIES FOR MENTAL TASK CLASSIFICATION USING ELECTROENCEPHALOGRAPHY SIGNALS

By

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CERTIFICATE OF AUTHORSHIP/ORIGINALITY

I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of the requirements for a degree except as fully acknowledged within the text.

I also certify that the thesis has been written by me. Any assistance that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

Signature of Candidate

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Abbreviations

ABS	:	Australian Bureau of Statistic
AC	:	Alternating current
ADC	:	Analog-to-digital converter
ALN	:	Adaptive logic network
ALS	:	Amyotrophic lateral sclerosis
ANN	:	Artificial neural network
AR	:	Autoregressive
ASSEP	:	Auditory steady state evoked potential
AT	:	Assistive technology
BCGA	:	Binary code genetic algorithm
BCI	:	Brain-computer interface
BLRNN		Bayesian logistic regression neural network
BLX-α	:	Blend-α crossover
BMI	:	Brain-machine interface
BOLD	:	Blood-oxygen-level-dependent
BSVM	:	Biased support vector machine
CM	:	Cross-mutated
CMRR	:	Common mode rejection
CNS	:	Central nervous system
CNV	:	Contingent negative variation

CRC	:	Cyclic redundancy check
DBI	:	Direct brain interface
DC	:	Direct current
deoxy-Hb	:	Deoxy-haemoglobin
DFT	:	Discrete Fourier transform
DNA	:	Deoxyribonucleic acid
DSP	:	Digital signal processing
DWT	:	Discrete wavelet transform
EA	:	Evolutionary Algorithm
ECG	:	Electrocardiography
ECoG	:	Electrocorticograpy
EEG	:	Electroencephalography
EIX	:	Extended intermediate crossover
EEMD	:	Ensemble empirical mode decomposition
EMD	:	Empirical mode decomposition
EMG	:	Electromyography
EOG	:	Electrooculography
ERD	:	Event-related desyncronization
ERD/ERS	:	Event-related desynchronization/synchronization
ERP	:	Event-related potential
ERS	:	Event-related synchronization
FES		Functional electrical stimulation
FFT	:	Fast Fourier transform
FIFO	:	First-in-first-out
FIS	:	Fuzzy inference system

fMRI	:	Functional magnetic resonance imaging
fNIRS	:	Functional near-infrared spectroscopy
FPSOCM	:	Fuzzy particle swarm optimization with the cross-mutated operation
FPSOCM-ANN	:	Fuzzy particle swarm optimization using cross-mutated operation of artificial neural network
GA	:	Genetic algorithm
GA-ANN	:	Genetic algorithm optimization of artificial neural network
GD	:	Gradient-descent
HHT-EMD	:	Hilbert-Huang transform using empirical mode decomposition
HHT-EEMD	:	Hilbert-Huang transform using ensemble empirical mode decomposition
HHT	:	Hilbert-Huang transform
HT	:	Hilbert transform
In-Amp	:	Instrumentation amplifier
IC	:	Integrated circuit
iEEG	:	Intracranial electroencephalography
IMF	:	Intrinsic mode function
IRQ	:	Interrupt request
ISM	:	Industrial, scientific and medical
ITR	:	Information transfer rate
LED	:	Light-emitting diode
LDA	:	Linear discriminant analysis
LFP	:	Local field potentials
LVQ	:	Learning vector quantization
MAC	:	Multiplier and accumulator

MEG	:	Magneto-encephalography
MLP	:	Multi-layer perceptron
MRI	:	Magnetic resonance imaging
MSE	:	Mean square error
NADA	:	Noise-assisted data analysis
NFB	:	Neurofeedback
OAA	:	One-against-all
OAO	:	One-against-one
oxy-Hb	:	Oxy-haemoglobin
PCB	:	Printed circuit board
PC	:	Personal computer
PET	:	Positron emission tomography
PSD	:	Power spectral density
PSO	:	Particle swarm optimization
RBF	:	Radial basis function
RCGA	:	Real-coded genetic algorithm
RF	:	Radio frequency
RFI	:	Radio frequency interference
RMP	:	Resting membrane potential
RTC	:	Real time clock
RTOS	:	Real-time operating system
SCP	:	Slow cortical potential
SCI	:	Spinal cord injury
SDAC	:	Survey of disability, ageing and carers
SNR	:	Signal-to-noise ratio

SMR	:	Sensorimotor rhythm
SPECT	:	Single photon emission computed tomography
SPI	:	Serial peripheral interface
SQUID	:	Superconducting quantum interference device
SSVEP	:	Steady state visual evoked potential
SVM	:	Support vector machine
TTD	:	Thought translation device
UART	:	Universal asynchronous receiver-transmitter
UIEA	:	Utah intracranial electrode array
UNDX	:	Unimodal normal distribution crossover
VEP	:	Visual evoked potential
WT	:	Wavelet transform

Abstract

Brain-computer interface (BCI) has been known as a cutting-edge technology in the current research. It is able to measure the brain activity directly instead of using the natural peripheral nerves and muscles and translates the user's intent brain activity into useful control signals.There is still a need for a technology for severely disabled individuals who suffer from locked-in syndromes, such as amyotrophic lateral sclerosis (ALS), cervical spinal cord injury (SCI) or tetraplegia and brain stem stroke. A brain-computer interface (BCI) could be used here as an alternative solution for control and communication. The main aim of this research is to develop a BCI system to assist mobility as hand-free technology for people with severe disability, with improved accuracy, which provides effective classification accuracy for wheelchair control.

Electroencephalography (EEG) is the chosen BCI technology because it is non-invasive, portable and inexpensive. Currently, BCI using EEG can be divided into two strategies; selective attention and spontaneous mental signal. For the selective attention strategy, BCI relies on external stimuli which might be uncomfortable for severely disabled individuals who need to focus on external stimuli and the environment simultaneously. This is not the case for BCIs which rely on spontaneous mental signals initiated by the users themselves. BCI that uses sensorimotor rhythm (SMR) is one of the examples of the spontaneous mental strategy. There have been many reports in research using SMR-based BCI; however, there are still some people who are unable to use this. As a result, in this thesis, mental task-based EEG is used as an alternative.

This thesis presents the embedded EEG system for mental task classification. A prototype wireless embedded EEG system for mental task BCI classification is developed. The prototype includes a wireless EEG as head gear and an embedded system with a wireless receiver. The developed wireless EEG provides a good common mode rejection ratio (CMRR) performance and a compact size with a low current consumption coin cell battery for power. Mental tasks data are collected using the prototype system from six healthy participants which include arithmetic, figure rotation,

letter composing and counting task with additional eyes closed task. The developed prototype BCI system is able to detect the dominant alpha wave between 8-13Hz during eyes closed. Using the FFT as the features extractor and artificial neural network (ANN) as the classifier, the developed prototype EEG system provides high accuracy for the eyes closed and eyes open tasks. The classification of the three mental task combinations achieve an overall accuracy of around 70%.

Also, an optimized BCI system for mental task classification using the Hilbert-Huang transform (HHT) feature extractor and the genetic algorithm optimization of the artificial neural network (GA-ANN) classifier is presented. Non motor imagery mental tasks are employed, including: arithmetic, letter composing, Rubik's cube rolling, visual counting, ringtone, spatial navigation and eyes closed task. When more mental tasks are used, users are able to choose the most effective of tasks suitable for their circumstance. The result of classification for the three user chosen mental tasks achieves accuracy between 76% and 85% using eight EEG channels with GA-ANN (classifier) and FFT (feature extractor). In a two EEG channels classification using FFT as the features extractor, the accuracy is reduced between 65% and 79%. However, the HHT features extractor provides improved accuracy between 70% and 84%.

Further, an advanced BCI system using the ANN with fuzzy particle swarm optimization using cross-mutated operation (FPSOCM-ANN) for mental task classification is presented. This experiment involves five able-bodied subjects and also five patients with tetraplegia as the target group of the BCI system. The three relevant mental tasks used for the BCI concentrates on mental letter composing, mental arithmetic and mental Rubik's cube rolling forward. Although the patients group has lower classification accuracy, this is improved by increasing the time-window of data with the best at 7s. The results classification for 7s time-window show the best classifier is using the FPSOCM-ANN (84.4% using FPSOCM-ANN, 77.4% using GA-ANN, 77.0% using SVM, 72.1% using LDA, and 71.0% using linear perceptron). For practical use of a BCI, the two channels EEG is also presented using this advanced BCI classification method (FPSOCM-ANN). For overall, O1 and C4 are the best two channels at 80.5% of accuracy, followed by the second best at P3 and O2 at 76.4% of accuracy, and the third best at C3 and O2 channels at 75.4% of accuracy.